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Improving Background Multivariate Normality and Target Detection Performance Using Spatial and Spectral Segmentation

(Invited Paper)

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Abstract—Target detection in reflective hyperspectral imagery generally involves the application of a spectral matched filter on a per-pixel basis to create an image of the target likelihood of occupying each pixel. Stochastic (or unstructured) target detection techniques require the user to define an estimate of the background mean and covariance from which to separate out the desired targets in the image. Typically, scene-wide statistics are used, although it is simple to show that this methodology does not produce sufficiently multivariate normal backgrounds, nor does it necessarily represent the best suppression of likely false alarms. This technique can be improved on by segmentation methods that selectively choose which pixels best represent the background for a particular test pixel and / or target spectrum. Here, several spatial and spectral segmentation techniques are presented and improved target detection performance over scene-wide statistics is shown for a common target in two data sets with different scene content. Results are presented in the form of Average False Alarm Rates and a Chi-squared goodness of fit measure of the background multivariate normality. Improvements are possible using segmentation methods over global estimation of background mean and covariance. However, the best method of background characterization depends strongly on the spatial and spectral characteristics of the target of interest and scene content.

I. INTRODUCTION

Target detection in hyperspectral imagery covering the reflective portion of the electromagnetic spectrum has long been a topic of interest [1]–[3]. Much work has been done investigating various *types* of detectors with the goal of optimum separation between the background and target spaces. This has produced two general families of detectors. Structured detectors characterize the background using a geometrical model (end-members or basis vectors) while unstructured detectors characterize the background using first and second order statistics [3]. Unstructured detectors are generally variations on the Matched Filter formalism that inherently makes three assumptions about the application of first and second order statistics to the target detection problem. First, the background is considered homogeneous and exhibits multivariate Gaussian behavior. Second, the covariance of the background spectrum providing the interference with the target signature is identical to the covariance of the background training pixels. Third, the target and background spectra must combine in an additive fashion [3]. These assumptions are not necessarily well met for globally computed means and covariances in hyperspectral imagery.

This work seeks to improve methods for background characterization by implementing various segmentation techniques [4] to better adhere to the assumptions described above. Spatial and spectral segmentation methods have been applied to various particular problems [1], [5]–[7]. Here, existing methods are implemented along with new methods, all of which are compared against a common target in two hyperspectral images of varying scene content.

This paper is organized in the following way. Section II presents the spatial and spectral segmentation methods for background characterization developed here. Section III describes the experiment conducted, including data used and metrics applied. Section IV presents the results of the experiment and Section V presents a summary of the conclusions drawn from this work.

II. BACKGROUND ESTIMATION METHODS

The unstructured detector used in this work is the Generalized Likelihood Ratio Test (GLRT) as derived by Kelly (1989). The GLRT requires estimates of the background mean spectrum and covariance matrix to suppress the background and highlight pixels containing targets. The GLRT as implemented here is given as

$$T_{GLRT} = \frac{\left(d^T \Sigma^{-1} x\right)}{\left(d^T \Sigma^{-1} d\right)\left(1 + x^T \Sigma^{-1} x\right)} \quad (1)$$

where T_{GLRT} represents the returned test statistic for a particular pixel, d is the desired target spectral vector, x is the test pixel spectral vector, both of which have been de-meaned with μ, the estimate of the background mean, and Σ is the estimate of the background covariance. Superscript T represents the vector transpose.

Of primary interest in this work is the estimation of μ and Σ. *Global estimation* of these quantities uses all pixels in the image, and can be shown to violate the assumptions of the matched filter described above. Also, assuming the target lies within the scene, global estimation includes the target spectrum into the characterization of the background degrading algorithm performance.

A. Spatial Segmentation

Spatial segmentation seeks to improve the background estimate by selection of a region that is either spatially proximal to the pixel under test, or selection of a large uniform area in the image that is believed to be target-free improving the assumptions of multivariate normality. The first spatial segmentation method was implemented as a sliding window similar to the original implementation of the RX algorithm [1], but using the GLRT detector above (eqn. 1). The algorithm was designed specifically to increase the multivariate normality of the background while also suppressing false alarms due to local backgrounds. As implemented here, four windows are identified for the spatial segmentation: a detection window, an exclusion window, a mean window, and a covariance window. The detection window is chosen as a single pixel giving each pixel under test had a unique background estimate. The exclusion window is a region around the test pixel(s) that is excluded to ensure that no target pixels are included in the estimation of the background statistics. The mean and covariance windows are as their names imply, windows over which the first and second order statistics are computed. Here the size of the covariance window is varied.

A second spatial segmentation scheme used a "target approach" method. Large, contiguous, single-class regions were pre-selected that were known to be target-free and were used to estimate the background mean and covariance. This method could be applied in the event that data were acquired "on approach" to the target region over an area similar in spectral class makeup. Specific target approach regions used here are described in Section III-A.

B. Spectral Segmentation

Spectral segmentation uses the spectral characteristics of the image pixels to cluster them into distinct classes. Background estimation can then be performed based on these spectral classes as opposed to the spatial regions as above. This method should be particularly effective for fully-resolved targets with "impersonator" (or spectrally similar) false alarms. Here the image was classified using the Stochastic Expectation Maximization algorithm with the Gaussian Maximum Likelihood as a discrimination function [9]. To investigate the effectiveness of background estimation with different segmentation methods independently from their ability to exclude target species, targets were perfectly excluded (using a target mask) from the classifications when estimating class covariances. Several methods for choosing the appropriate class for background mean and covariance estimation are possible and those developed here are described below and presented in Table I.

TABLE I
NAMING CONVENTION FOR THE SPECTRAL SUBSETTING METHODS.

	Covariance Estimation Method			
	Target Guided	Pixel Guided	Neighbor Guided (Mode)	Neighbor Guided (Mixed)
Local Mean	LMTG	LMPG	LMNG-M	LMNG-X
Class Mean	CMTG	CMPG	CMNG-M	CMNG-X

Two methods for estimation of the background mean are considered. The *Local Mean* method is identical to the above-mentioned spatial sliding window method. The *Class Mean* method estimates the background mean as the spectral mean of the pixels in the class to which the test pixel was assigned.

There are several ways to choose a training set to estimate the background covariance. *Target Guided* estimation uses the pixels in the class that is spectrally closest (in a Mahalanobis distance sense) to the target pixel. This assumes that the pixels spectrally most like the target are the most likely false alarms in the image and should be suppressed. *Pixel Guided* covariance estimation is similar, but the pixels in the class to which the test pixel is assigned are used in the calculation. *Neighbor Guided (Mode)* uses the pixels in a torus, approximately twice the size of the target, around the test pixel. The classes to which the pixels in this torus have been assigned are polled, and the covariance of the class that is most common is used. *Neighbor Guided (Mixed)* uses all the pixels in the torus, but computes a covariance based on a mixture of the class covariances (weighted by the class representation in the neighborhood) represented in the torus. The Neighbor Guided methods substitute the well-formed statistics from pre-clustering with the more variable statistics of a sliding covariance window. This may negatively impact detection performance, though, especially along transition windows.

III. EXPERIMENT DESCRIPTION

A. Data

Test data used here were collected with the HYDICE airborne hyperspectral sensor [10] and is part of a collected set of data, including ground truth measurements and target masks, known as the "Canonic Data Set". Two scenes were used, a "Forest" scene and a "Desert" scene. Images of each are shown in Figure 1. The image contains 210 spectral bands. After removal of spectral channels in strong atmospheric absorption features and those containing strong sensor artifacts, 145 spectral channels were left for processing. The radiometrically calibrated cubes were converted to surface reflectance using the large calibration panels in the image as reference targets for the Empirical Line Method. Several man-made targets were placed in each scene during the respective collections. Here, one vehicle target was used as the target of interest to compare how the different backgrounds in the two scenes affected the ability to detect the target using the methods described above. Target masks accompanying the data set were used to identify fully resolved target pixels and sub-pixel targets.
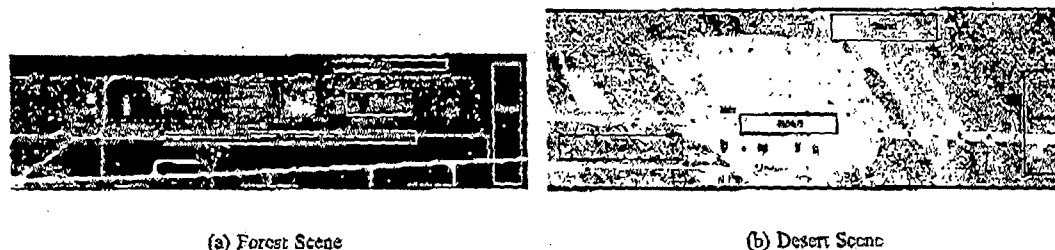
(a) Forest Scene   (b) Desert Scene

Fig. 1. Data used in the experiment with Target Approach regions highlighted.

B. Performance Metrics

Two metrics were used to characterize the background characterization methods described above. A measurement of the Multivariate Normality (MVN) of the background was computed to assess the normality achieved in the background segmentation method. Also, algorithm detection performance was measured with an Average False Alarm Rate (AFAR). The AFAR calculation used the target mask to identify fully resolved and sub-pixel target pixels. All AFAR calculations are on a *per-pixel* basis, as opposed to a *per-target* basis.

To compute the AFAR for each background characterization method, Receiver Operation Characteristic (ROC) curves were made for the target and each method based on the target pixel mask. The AFAR was calculated as an estimation of the area above the ROC curve. For this work, a full AFAR was computed.

The multivariate normality (MVN) of the background used was estimated through use of a chi-squared test [11] to test each band of the image separately. In the chi-squared test, a plot is constructed comparing the familiar Mahalanobis distance of the deviation from the mean with the appropriate chi-squared distribution. For multivariate normal data, the two metrics will be related by a slope of unity with zero bias. The Mahalanobis distances are ordered smallest to largest and plotted against the upper percentiles of the chi-squared distribution. The the "goodness of fit" (GoF) of the data to the normal distribution is determined through a correlation coefficient test, reducing the curve to a single metric, where a *lower* value represents greater MVN [4].

IV. RESULTS

Results are shown in Figure 2 demonstrating the Multivariate Normality characteristics for each background chosen in each scene. Here, *lower* values represent a "more normal" background. MVN Goodnes of Fit values for the three worst cases are beyond the scale of the figure, and these methods clearly do not adhere to the assumption of a multivariate normal background. For both cases, the scene-wide background is far from multivariate normal and some of the spectrally-identified classes stray from normality as well. These classes are generally the "bright" classes (sand classes in the Desert scene and light ground and grass in the Forest scene). However, all other methods of segmenting the background produce

classes of approximately equal MVN (as measured by the metric employed here). In the *Neighbor Guided* spectral pre-clustering techniques, though, if the neighborhood of the test pixel contains several pixels in the classes exhibiting poor MVN, this will impact the results for that pixel.

Figure 3 shows the Average False Alarm Rate (AFAR) results for the various methods used to segment the background. Several conclusions can be drawn from these results demonstrating how techniques used to detect the same target in two different scenes can have dramatically different results. First, the full pixel targets in the Forest scene were obviously of relatively high contrast against the background as all methods detected the full pixel targets almost perfectly. This is not the case for the Desert scene where, while the performance against the full pixel targets is generally good, several techniques have difficulty detecting the target. Conversely, the sub-pixel targets were generally detected with lower AFAR in the Desert scene than in the Forest scene. Here, false alarms are expected to be due to local spectral mixture of the signal. These segmentation methods applied here were better able to suppress the local mixture FAs in the Desert scene than in the Forest scene. The *Cluster Mean, Neighbor Guided - Mixed* method performed particularly poorly for the Desert scene - dramatically worse than any other method, and significantly worse than as applied to the Forest scene. Clearly, in the Desert scene the target was located in a neighborhood where a mixture of covariances impacted the target detection. This is contrasted with the *Cluster Mean, Neighbor Guided - Mode* method which was one of the best performers for this target in both scenes.

V. SUMMARY AND CONCLUSIONS

Several methods for spatial and spectral segmentation of hyperspectral data were presented with the aim of better understanding how to best estimate the background statistics to optimize target detection performance. A common target was used in two scenes of different spatial and spectral clutter complexity. It is shown that improvements in the Multivariate Normality of the scene-wide background using either spatial or spectral segmentation is possible, although in these cases this is not the limiting factor affecting performance. For the same target identical detection methods show different performance across the two scenes. Based on this (and results from a larger test set) it is currently unclear how to predict *a priori* what is the *best* method for background characterization. It is likely
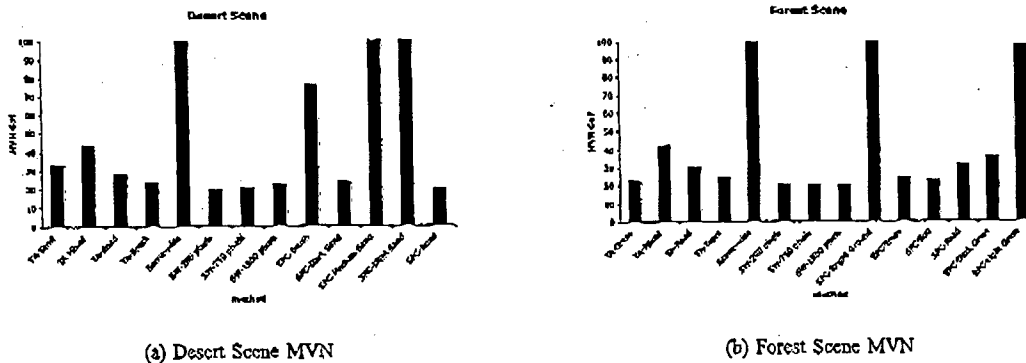
(a) Desert Scene MVN   (b) Forest Scene MVN

Fig. 2. Multivariate Normality Test Results: TA - target approach regions; SW - sliding window sizes; SPC - spectral pre-clustering methods.

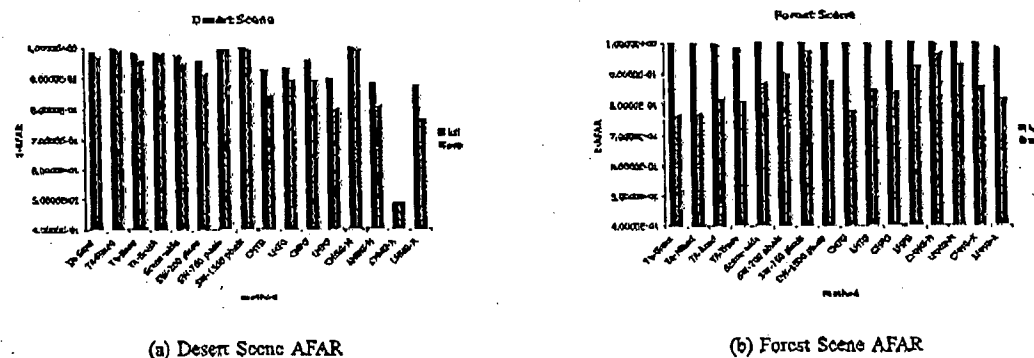(a) Desert Scene AFAR   (b) Forest Scene AFAR

Fig. 3. Target Detection Performance: TA - target approach regions; SW - sliding window sizes; SPC - spectral pre-clustering methods. Note that the y axis is 1-AFAR so values close to one represent good performance.

that this is both target and scene dependent, and more work needs to be done to identify the target and scene characteristics that determine the optimal method.

DISCLAIMER

The views expressed in this article are those of the authors and do not reflect the official policy or position of the United States Air Force, Departments of Defense, or the U.S. Government.

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